Application of computational models in Next Generation Risk Assessment activities at Unilever

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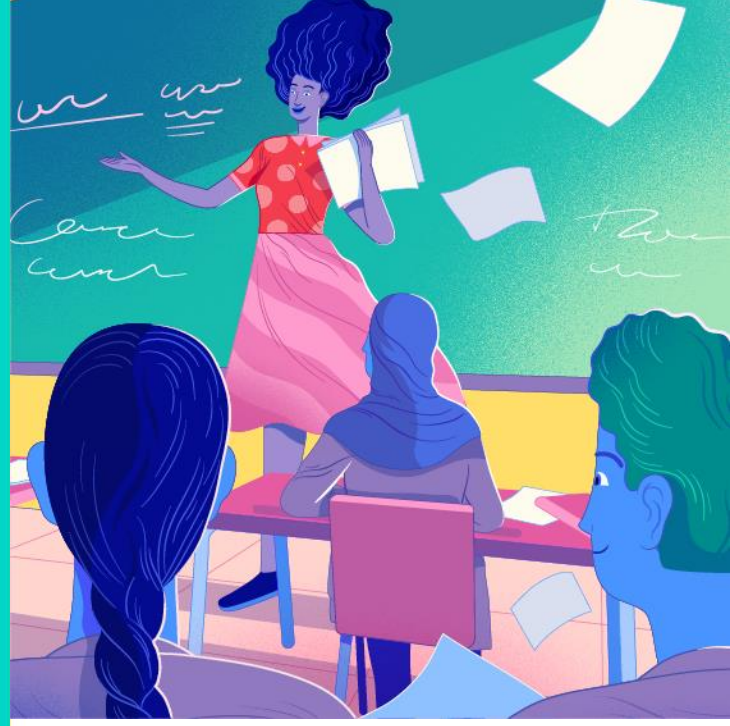

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Outline

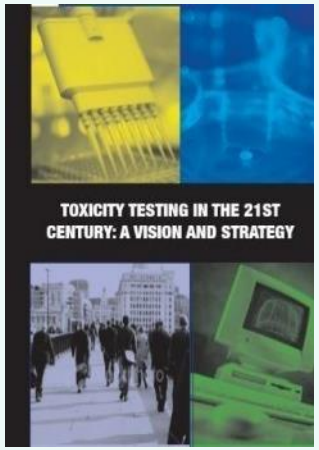
- Introduction
- Computational models applied in NGRA in Unilever
  - Physiologically Based Kinetic (PBK) modelling
  - Dose Response Modelling
  - High Throughput Transcriptomics (HTTr) Dose response analysis
  - Bayesian Method
  - Expert Knowledge Elicitation
- An example
- Summary and discussion

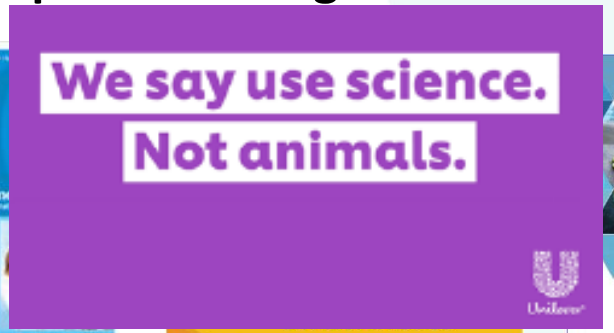
Can we use a new ingredient safely and how do we know?

Can we safely use x% of ingredient y in product z?

NGRA is defined as an exposure-led, hypothesis-driven risk assessment approach that integrates New Approach Methodologies (NAMs) to assure safety without the use of animal testing

We address the above question using Next Generation Risk Assessment





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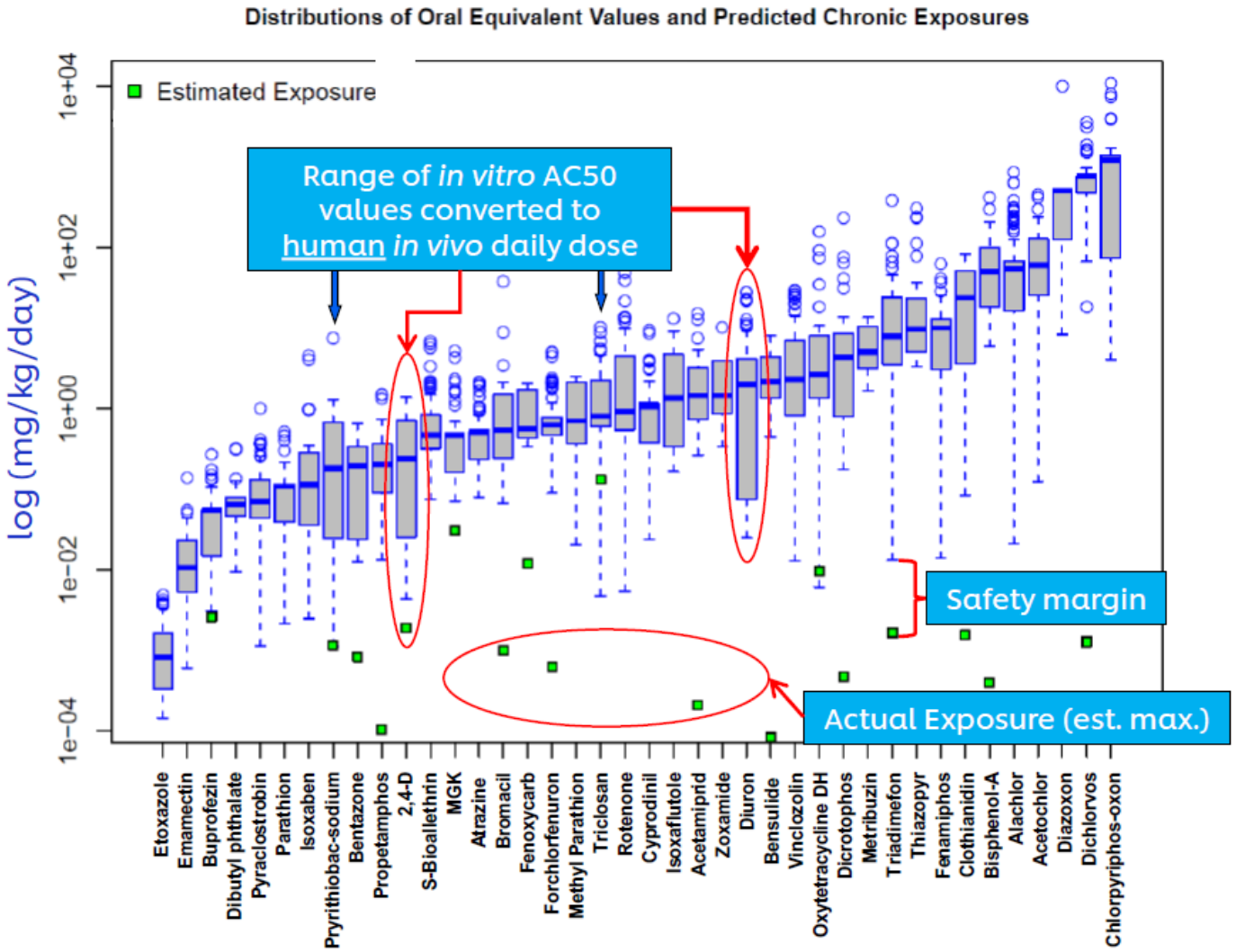
NGRA: Protection not Prediction



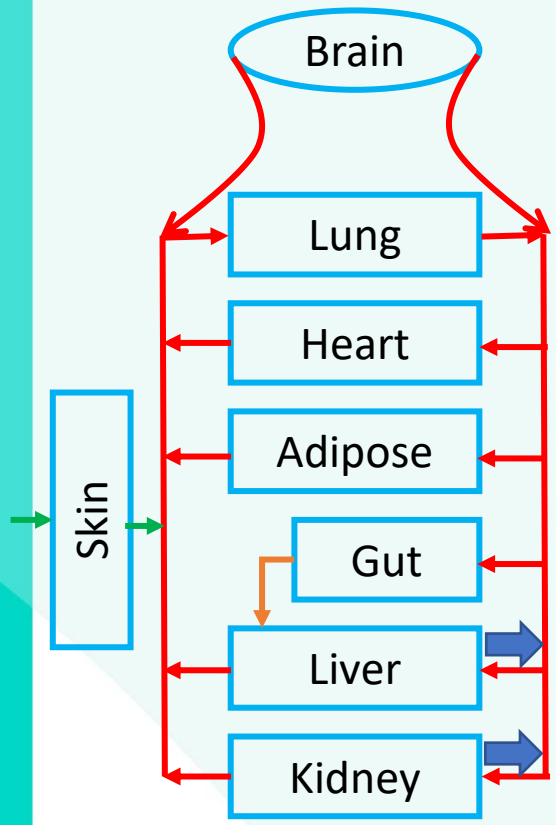
The hypothesis underpinning this NGRA is that if no bioactivity is observed at consumer-relevant concentrations, there can be no adverse health effects.

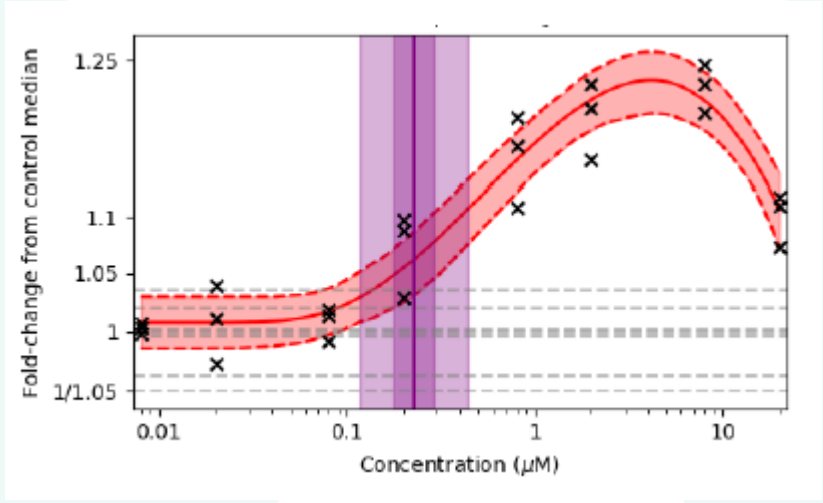
At no point does NGRA attempt to predict the results of high dose toxicology studies in animals

NGRA uses new exposure science and understanding of human biology

Graph from Rusty Thomas EPA, with thanks. Rotroff *et al* (2010) Toxicological Sciences , **117**, 348-358

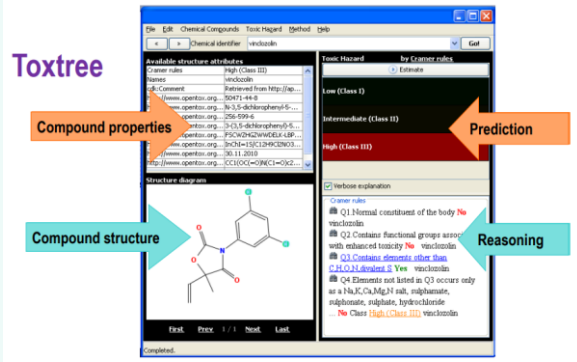
Computational models in NGRA – some examples





Bayesian Statistics

$$P(\theta|Data) \propto P(\theta)*P(Data|\theta)$$



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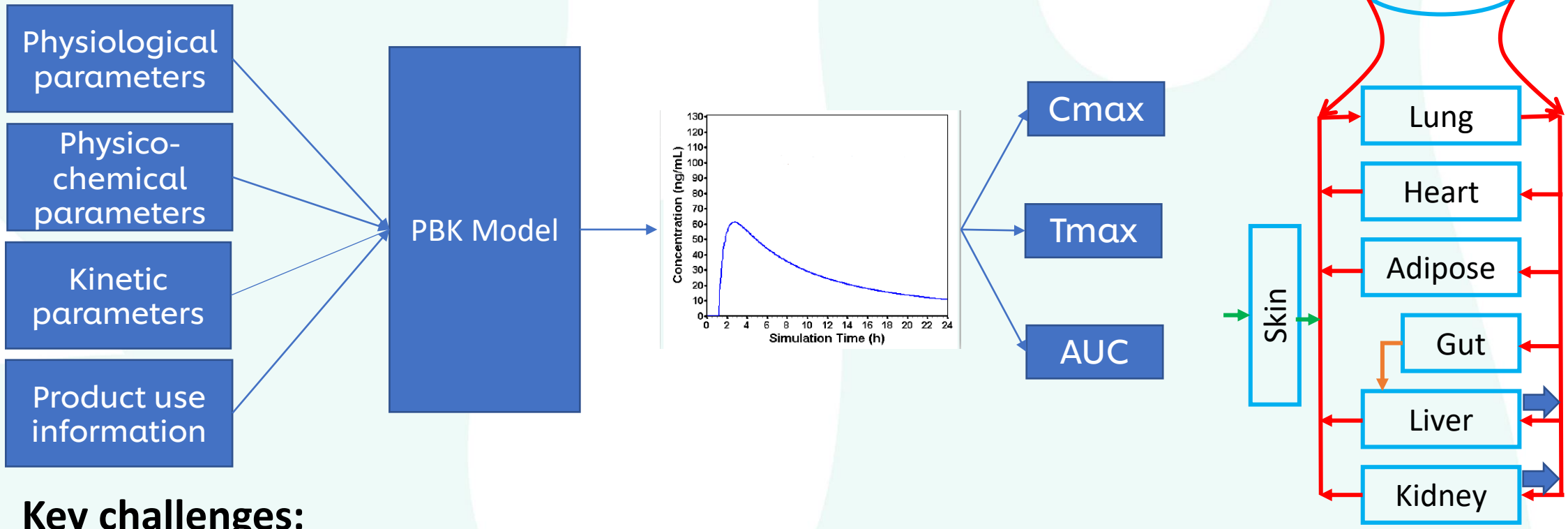
Computational models 1- Physiologically Based Kinetic (PBK) modelling

Aim:

According to ADME properties of a certain chemical, predict its concentration in different organs/tissues in human body after exposure to the chemical via different exposure route, e.g., oral, skin and inhalation



Key challenges:

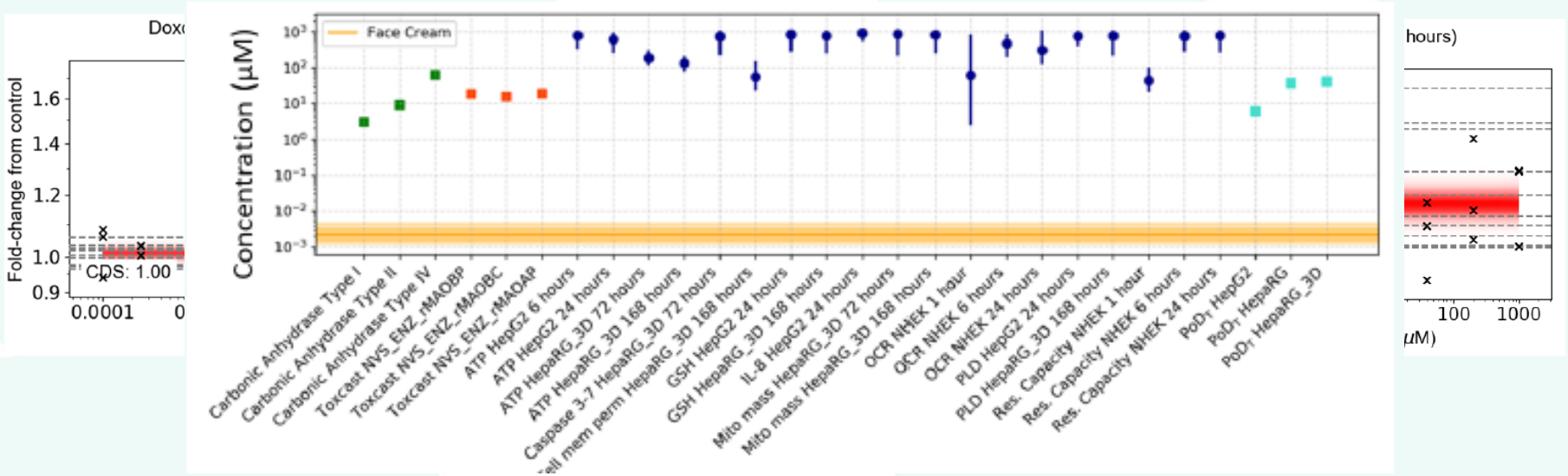
- Understanding ADME mechanism
- Parameterisation

Li *et al* (2022) *Toxicology and Applied Pharmacology*, **442**, 115992

Computational models 2 - Dose Response Modelling

Aim:

- Using the dose and response data from a certain in vitro assay to derive a Point of Departure (PoD) regarding a certain biomarker after exposure to a certain chemical.
- By combing PoDs from different assays regarding different biomarkers, the overall bioactivity of the chemical can be described, which is then compared with exposure derived from PBK modelling, so that a safety decision can be informed.



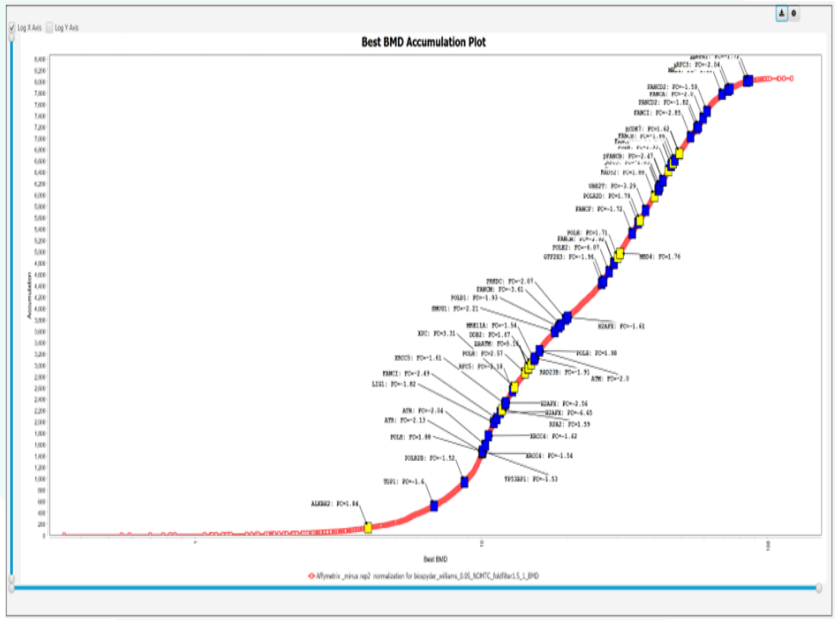
Key challenges:

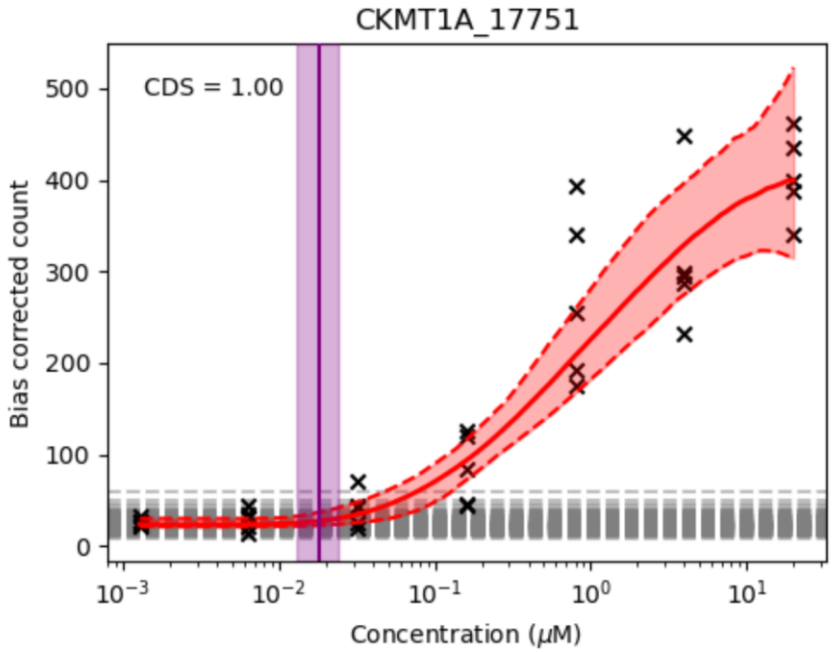
- Whether there is a response?
- At what dose there is a response?
- Uncertainty

Baltazar *et al.*, (2020) *ToxicolSci***176**, 236–252

Computational models 3 - High Throughput Transcriptomics (HTTr) Dose response analysis

Aim: based on the gene expression data, provide a broad biological perturbation concentration response measure (POD) and indicate mechanistic information as a hazard characterisation. **Assumption:** there is no adverse effect without gene expression changes





Challenges:

- Multiple parameter thresholds need to be defined that impact on overall analysis and sensitivity, e.g.,
  - depth of sequencing & replicates impact power of experiment
  - No. of cell lines – overall biological coverage
  - fold change/p-value/BMR factor filters, choice of models for dose response, genes vs pathways – a matrix of options with best set(s) still currently being assessed.
- Transparency in sharing complex assay with complex bioinformatic workflows to enable replication. OECD Transcriptomic Reporting Framework (TRF)

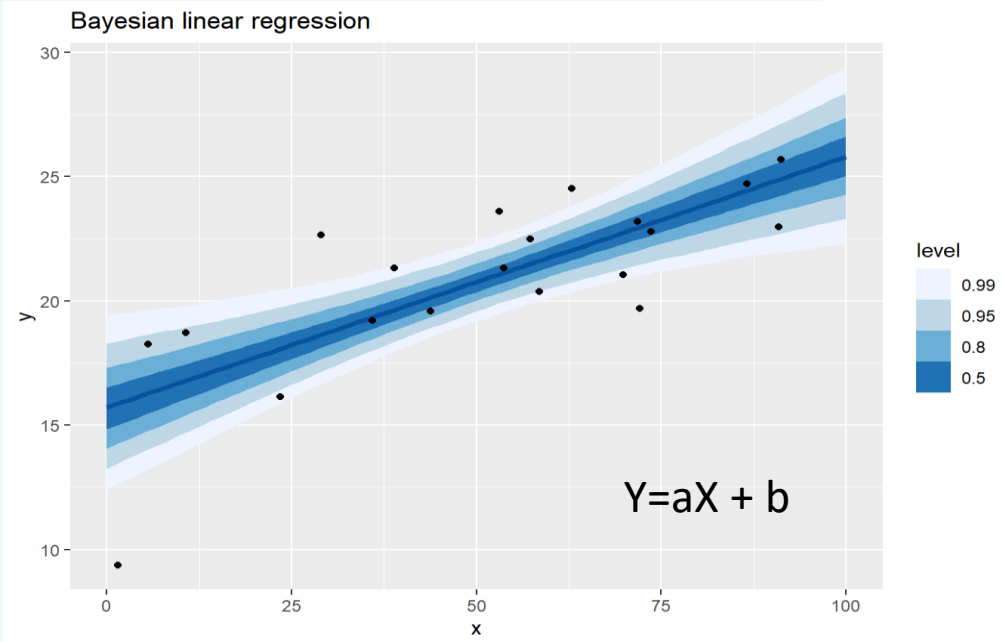
Computational models 4 – Bayesian statistics

Aim:

- Using (newly) observed/available data to update the probability distribution of parameters in a mathematical model based on
  - 1) the prior probability distribution of the parameters before observing the data, and
  - 2) a likelihood function describing how likely the data can be observed given certain values that the parameters take.
- Can be used in many different areas, such as analysing dose response relations.

Bayesian Statistics

$$P(\theta|Data) \propto P(\theta)*P(Data|\theta)$$



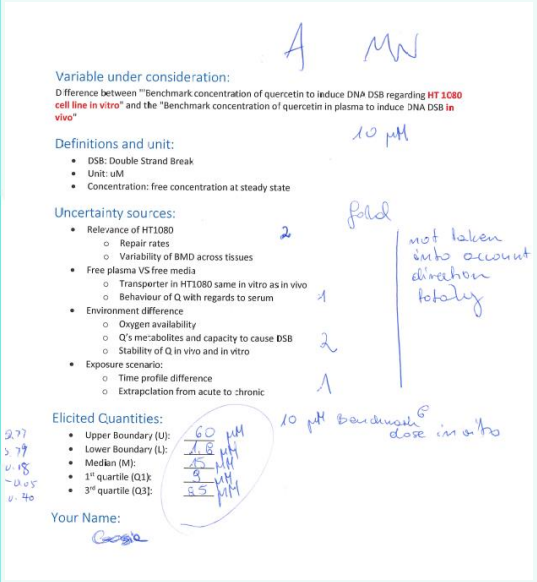
Key challenges:

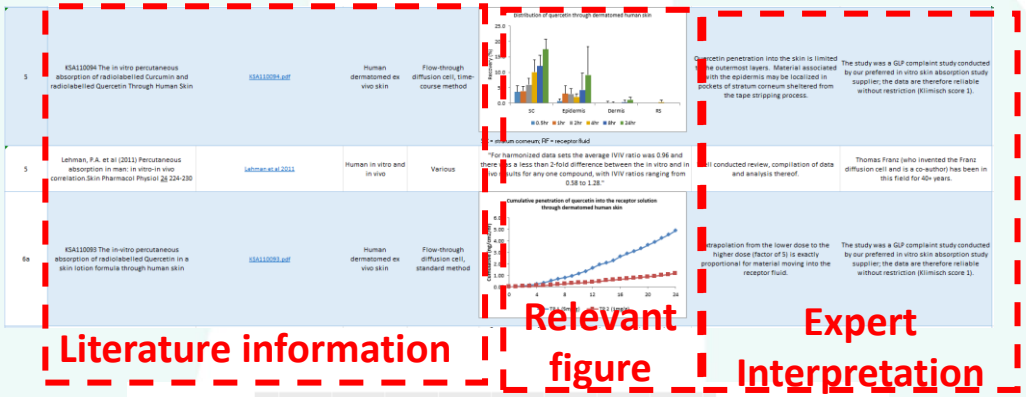
- Specify prior distribution of parameters and a likelihood function

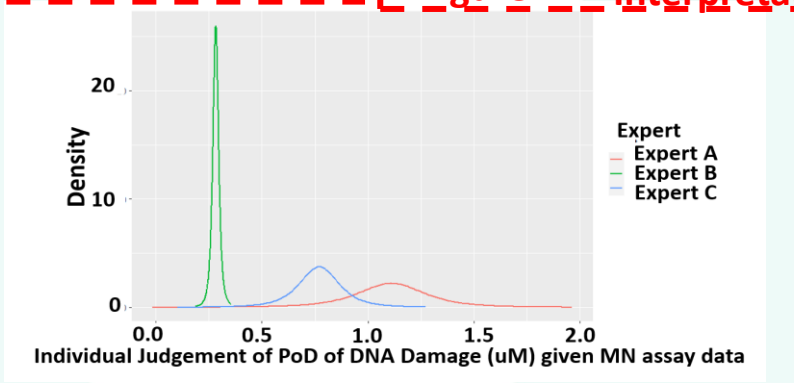
Computational models 5 - Expert Knowledge Elicitation

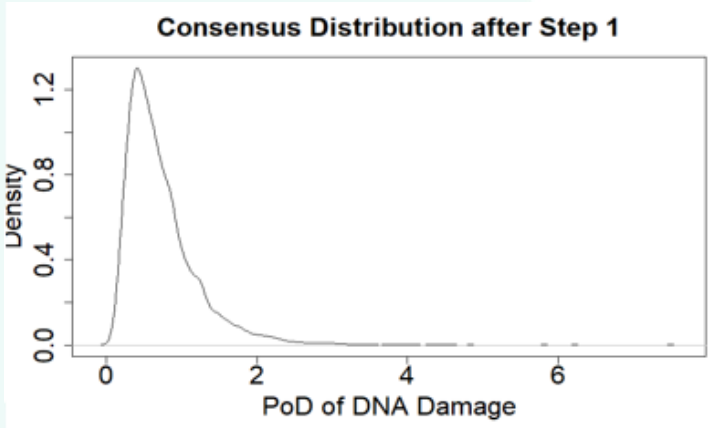
Aim:

- Handling the situation where there is not enough data to adequately inform the risk assessment decision but there is some extent of data and knowledge exist which can be used to inform the decision.
- Elicit experts' knowledge in a way that common cognitive and psychological biases are minimised by following a strict protocol with rational of the experts' judgment explicitly justified and documented.





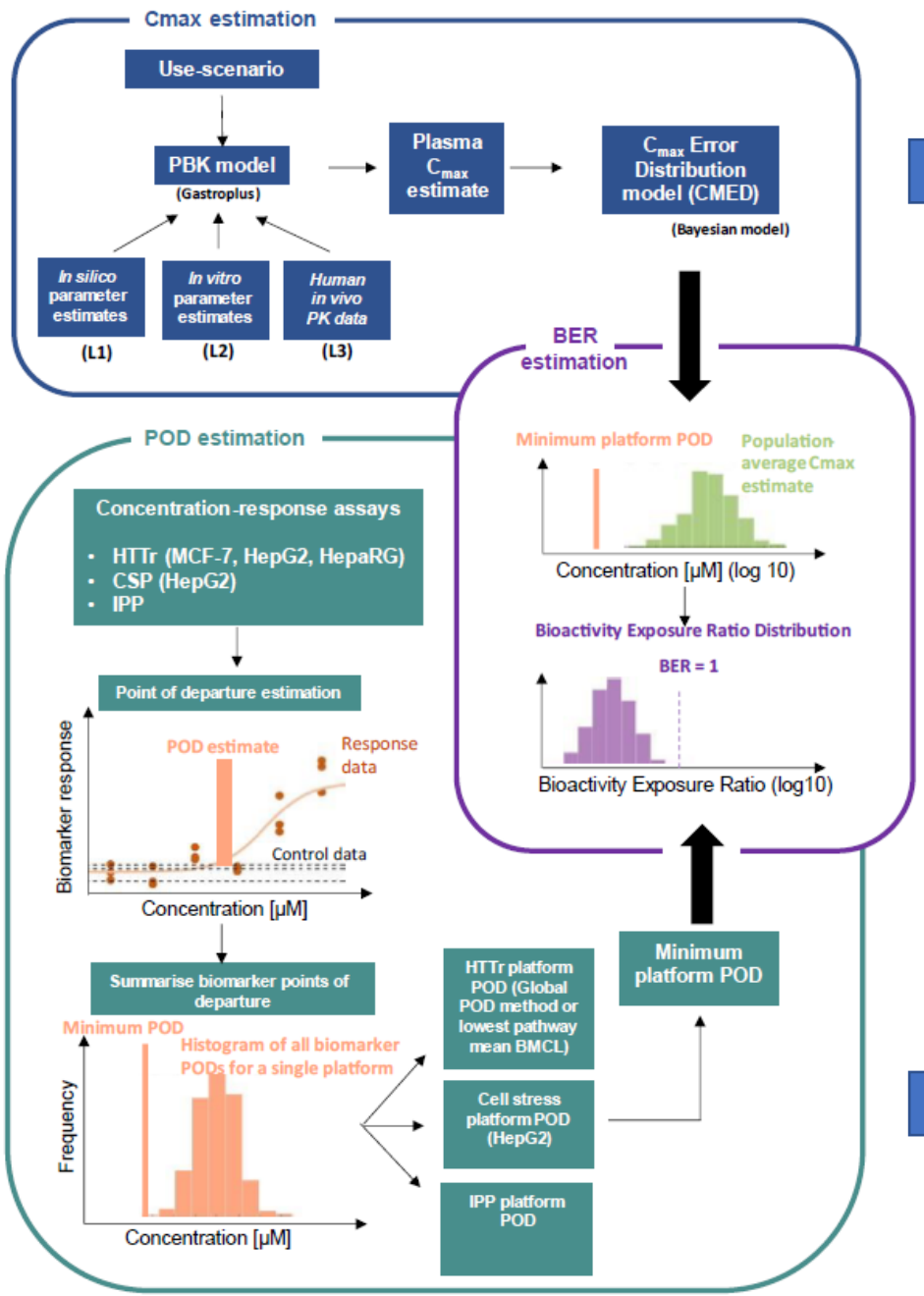




Key challenges:

- Elicitation process design and facilitation

Example – evaluating protectiveness of safety assessment using non animal methods



Estimating the internal exposure of a chemical based on a given use-case scenario, using 3 different levels of information:

- In silico informed parameters only
- + some in vitro informed parameters
- + some in vivo informed parameters

Are Non-animal Systemic Safety Assessments Protective? A Toolbox and Workflow

Outputs from these modules are combined in the third module to estimate the Bioactivity Exposure Ratio (BER)

Estimating the various Points of Departure (PODs) based on *in vitro* bioactivity data using three of the *in vitro* bioactivity platforms

- High-throughput transcriptomics
- A cell stress panel
- *In vitro* pharmacological profiling

Middleton *et al.*, (2022) *ToxicolSci*, **189(1)**, 124-147

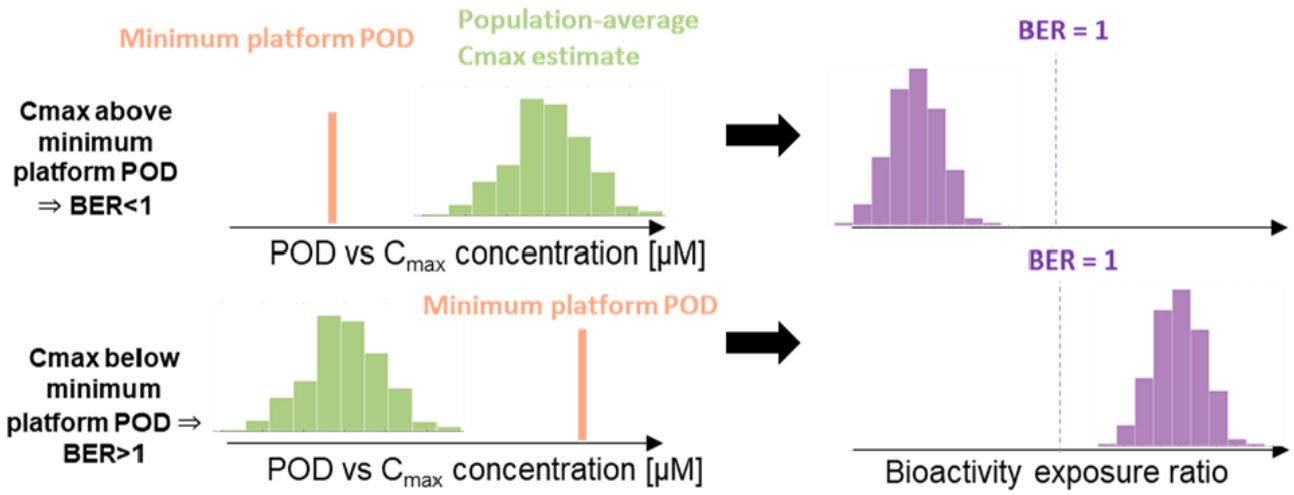
Example – evaluating protectiveness of safety assessment using non animal methods

Step 1: Define Benchmark chemical-exposure scenarios

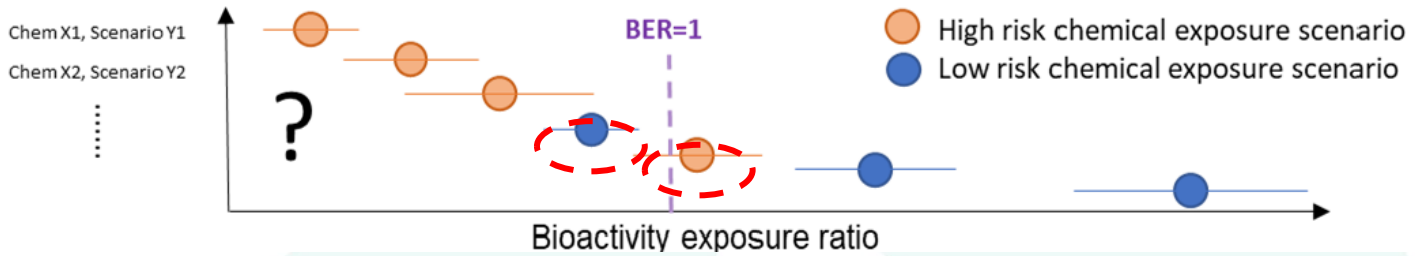
Chemical	Exposure scenario	Risk category
Chem X_1	Scenario Y_1	Low/High
…	…	…
Chem X_n	Scenario Y_m	Low/High

Step 2: Apply NAM tools to generate bioactivity and exposure data for PoD and Cmax estimation

Step 3: estimate minimum platform PoD and the Cmax to calculate the BER



Step 4: benchmark BER against risk category for each exposure scenario in Step 1



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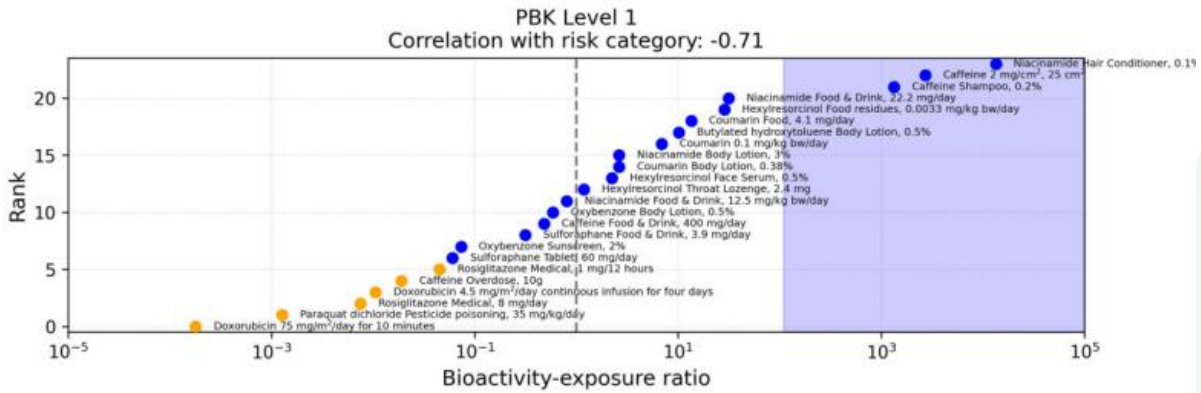
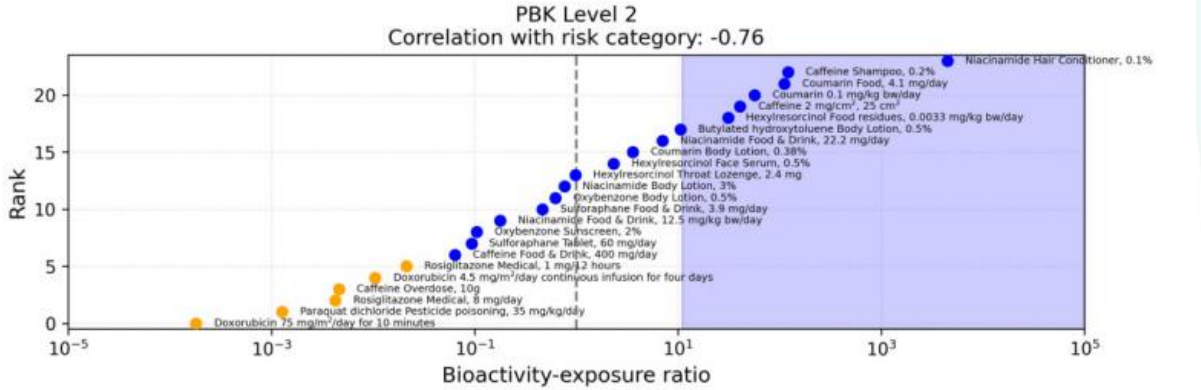
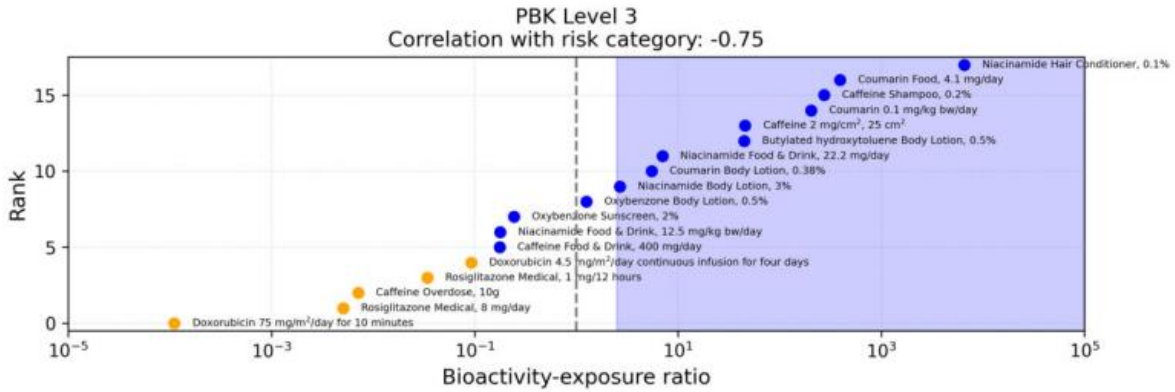
Example - evaluating protectiveness of safety assessment using non animal methods







Protectiveness: The proportion of high-risk scenarios not identified as low risk

Utility: The proportion of low-risk benchmark chemical scenarios correctly identified as such

PBK Level	Empirical Utility	Empirical Protectiveness
1	3/18 (17%)	6/6 (100%)
2	6/18 (33%)	6/6 (100%)
3	9/13 (69%)	5/5 (100%)

Middleton *et al.*, (2022) *ToxicolSci*, **189(1)**, 124-147

Discussion

- A number of computational methods have been applied to NGRA

- An example is briefly introduced which applies some of the methods above to demonstrate the protectiveness of systemic safety assessment using non animal methods

- In general, computational models are increasingly applied across different areas (bioactivity and exposure) within NGRA.

- We need to work hard to ensure methods are robust and acceptable

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